Development and field testing of a time synchronized system for multi-point displacement calculation using low cost wireless vision based sensors

Development and field testing of a time-synchronized system for multi-point displacement calculation using low cost wireless vision-based sensors

Darragh Lydon, Myra Lydon, Jesús Martínez del Rincón, Su Taylor, Des Robinson, Eugene O'Brien, Necati Catbas.

***Abstract*—This paper presents a contactless multi-point displacement measurement system using multiple synchronized wireless cameras. Our system makes use of computer vision techniques to perform displacement calculations, which can be used to provide a valuable insight into the structural condition and service behaviour of bridges under live loading. The system outlined in this paper provides a low cost durable solution which is rapidly deployable in the field. The architecture of this system can be expanded to include up to ten wireless vision sensors, addressing the limitation of current existing solutions limited in scope by their inability to reliably track multiple points on medium and long span bridge structures. Our multi-sensor approach facilitates multi-point displacement and additional vision sensors for vehicle identification and tracking that could be used to accurately relate the bridge displacement response to the load type in the time domain. The performance of the system was validated in a series of controlled laboratory tests. This research will significantly advance current vision-based Structural health monitoring (SHM) systems which can be cost prohibitive and provides a rapid method of obtaining data which accurately relates to measured bridge deflections.**

***Index Terms*— Computer Vision, Feature Extraction, HD Video, Image Motion Analysis, Image Processing, Motion Estimation.**

I. INTRODUCTION

FACILITATING OVER 90% of motorized passenger travel and 65% of domestic freight, the road network is the most popular means of transport in the United Kingdom (UK). Currently UK transport infrastructure is rated as second worst among the G7 countries and there is a bridge maintenance backlog valued at £3.9bn. According to the 2017 Infrastructure report card, the corresponding figure in the USA is $123bn resulting in 188 million daily trips across structurally deficient bridges [1]. In the UK, the budget for core bridge maintenance has been reduced by up to 40% in recent years [2]. This budgetary shortfall means that cost effective and accurate structural information on bridge condition is becoming increasingly important. According to literature [3], the prevalent method for bridge monitoring continues to be visual inspections which can be highly subjective and differ depending on climatic conditions. This study goes into further detail on the efficacy of routine and in-depth inspections and determines that most inspection teams fail to determine bridge condition accurately. A recent study has indicated that bridge inspections vary in quality and are not always carried out by a senior engineer, with many companies outsourcing the inspections to untrained individuals [4].

Structural Health Monitoring (SHM) systems provide a valuable alternative to traditional inspections and overcome many of the previous limitations. SHM can provide an unbiased means of determining the true state of our ageing infrastructure. Sensor systems are used to monitor bridge deterioration and provide real information on the capacity of individual structures, hence extending the safe working life of bridges and improving safety. Monitoring of the displacement of a structure under live loading provides valuable insight into the structural behaviour and can provide an accurate descriptor of bridge condition. However, to monitor deterioration over time it is vital that the cause of displacement is also understood. Relating real time displacement along the span of a bridge to load type and location provides an opportunity to accurately identify localised damage within the structure.

Displacement can be measured using traditional sensors such as LVDT's. These instruments require contact with the bridge structure to obtain measurements, and an independent and rigid

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support system, which can be difficult in in many field applications. Accelerometers provide a promising alternative. The drawback with the usage of accelerometers is that they can be vulnerable to numerical error from double integration and initial condition analysis [5]. Laser vibrometers can provide an accurate measurement at a single monitoring location, with the disadvantage of not providing the flexibility of measurement available in vision systems due to being required to be fixed at a single point throughout measurement. Global Position Systems (GPS) can also be used for displacement calculation, but the accuracy of the system is not comparable to that of other systems, with the majority of commercial systems only capable of obtaining a resolution at centimetre resolution and far away from sub millimetre [6]. Traditional sensors also have challenges in evaluating displacement of a structure as a reaction to live loading, or to be accurately synchronized to this loading due to sensor setup and LVDT or slide wire potentiometer internal mechanics.

II. Computer vision based Sensors for Structural Health Monitoring

There are numerous examples in the literature of the efficacy of Computer Vision as a tool for SHM. In [7] the authors developed a low cost contactless system for the monitoring of displacement of a bridge structure; where results comparable to LVDT were obtained at distance of approximately 30 m. These readings are useful for displacement calculation but the requirement of having a laptop computer connected to the camera used for obtaining video images is restrictive in rural field applications. The capabilities of a Computer Vision system to monitor movement of a stadium structure under severe crowd loading has been proven, indicating its suitability to monitor structures under dynamic loading[8]. There are additional examples of vision-based displacement calculation in [9] and [10].

The work discussed above is all in single point displacement calculation, which is unsuitable for the monitoring of long span bridges when deflection profile is to be determined. There are two approaches to multipoint displacement measurement using cameras. The first approach is demonstrated in [11]. This research involves the selection of multiple displacement points in the viewpoint and using them to calculate multiple displacements, with the drawback of decreasing the resolution of the system as less detail of the points are available, especially for medium to long infrastructures. The concept of multiple points from a single camera's viewpoint has been expanded upon using a high resolution camera [12]. However, since no traditional sensors were used as a means of comparison in this research, it is difficult to verify the real accuracy of the system when deployed in the field. The other approach to multipoint displacement calculation involves the use of multiple synchronized cameras. Early work in this area was carried out in [13], where multiple personal computers (PCs) were used to control camcorders in a master-slave relationship. This system is based on estimating the time lag between master and slave computers and is also dependent on having the cameras controlled by a PC at all times, which are severe constraints for practical applications. This research is built upon in [14], with a more advanced version of the synchronization system being used. The inherent disadvantage of a frame grabber and PC being required for connecting the cameras limits the scope of the system for field deployments due to power consumption and difficulties with cabling cameras to the computers.

Previous research has shown that Computer Vision is viable as a method of displacement calculation. The increase in resolution of small, durable action cameras has led to their usage as a means of displacement calculation, as shown in [15]. Previous work in this area by the authors of this study has proven that our system is viable for usage in the laboratory and in field trials, with accurate results obtained compared to traditional sensors. The results obtained in field trials in this study were 0.952053 correlation coefficient(CC) and 0.0314 Root Mean Square Error (RMSE) when comparing vision based results to traditional displacement sensors.

This paper aims to expand on that work by implementing this algorithm in tandem with multiple time-synchronised high-resolution action cameras. This will provide a greater flexibility in monitoring locations on bridge structures, and allow the development of a time-synchronized, portable, wireless easy-to-use Computer Vision system for SHM which has been validated in laboratory trials and field experiments.

III. Development of a Wireless Vision Based Sensor Network for Structural Assessment

As previously mentioned vision-based sensors provide a completely contactless means of displacement measurement of structures. In many cases the vision sensor is built into a specialist camera and controlled by use of a laptop computer and frame grabber apparatus. These systems can be cost prohibitive and require onerous site set-up and wiring arrangements. This research has been based on the development of a low cost and easy to deploy system using the commercially available action cameras commonly known as "GoPros" [16]. In general vision-based monitoring, a camera is set up on a tripod at a stationary location in sight of the bridge. The vision sensor is used to record a series of images of a structural element of the bridge under live loading, usually at a minimum frame rate of 25 frames per second (fps). A significant advantage of the system is its ability to measure displacement at any location along the span of the bridge from one stationary camera location. The purpose of multi-point measurement is to provide more accurate information on bridge condition. A greater number of data points enables a more detailed assessment of the bridge behaviour under live loading due to the creation of multiple influences or influence surface. A change in the behaviour under certain load types can then be used to detect and localise damage in the structure.

A. *Hardware configuration:*

1) *Camera Modification*

GoPro vision sensors provide a low-cost, high resolution (up to 4K) solution for the capture of data. Additionally, their portability and wireless functionality for camera control offer a significant advantage. These cameras are resistant to adverse environmental conditions such as rain, making them practical for long term deployment in the field. The disadvantage of using GoPros for bridge monitoring is that the standard GoPro lens has a limited focal length, rendering them less suitable for accuracy over long distance monitoring of structures. Research was carried out into potential modifications to the camera to add long distance monitoring capability. A solution was found using a modification kit for the GoPro: Ribcage [17]. The Ribcage adds functionality for the attachment of C or F- mount zoom lenses to a GoPro. This allows usage of the GoPro as a long-distance monitoring tool. A Computar 1/2″ 25-135mm F1.8 C-Mount [18] lens was attached to the GoPro for the testing detailed in the following sections. This lens was chosen because it is capable of being fitted directly to a tripod whle attached to the GoPro, allowing for a stable mounting of the camera in laboroatory/ field trials. The hardware configuration for the test is shown in Fig 1, with an example of the camera mounting confirguration shown in Fig 2. The GoPro was controlled during testing using the Capture App [19] for smartphones provided by GoPro, with footage saved to microSd cards for later transfer to a PC for post processing.

Fig 1 Hardware specification, from left to right. GoPro Hero 4 black, Ribcage Lens Modification and Computar ½" 25-135mm F1.8 C-Mount lens

Fig 2 Camera mounting configuration for laboratory and field trials

2) Synchronization Hardware

The system that was chosen to provide time synchronization for the GoPro systems is known as Syncbac [20]. This GoPro accessory can be attached to the extension port of the GoPro and embeds timecode data into each frame recorded by the GoPro. Analysis of this metadata allows for synchronization of recordings obtained by the system using a solution developed by the authors in C++ in Microsoft Visual Studio. The Syncbac sends live timecode data via Radio Frequency (RF), with a range of 30-60m. There is also functionality available for units to be initially synchronized with a master unit before handling timecode insertion without any additional information being provided. The range of the system can also be extended to 150-180m by use of a pulse: [21], which allows for greater deployment range in addition to wireless control of all units via the Blink Hub app [22]. The Syncbac system also allows for wireless remote control of the cameras via PC/smartphone app, meaning the cameras can be placed in areas not traditionally available for bridge monitoring using Computer Vision.

B. Software and algorithm development for wireless vision-based sensor

A requirement of all vision-based SHM systems is intensive post processing of captured images into accurate bridge displacement responses [23]. For the system developed in this research, feature-based tracking was selected due to being more robust and reliable than Digital Image Correlation(DIC) approaches when paired with a reliable feature extraction technique, with similar precision [24]. The processing framework is composed of three main blocks, as shown in Fig 3.

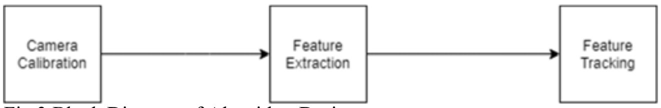

Fig 3 Block Diagram of Algorithm Design

1) Camera Calibration:

Camera Calibration is a method of determining the intrinsic and extrinsic parameters of the camera used to record the structure motion, to remove lens distortion effects and to provide a scaling factor for the conversion from pixel units to engineering units. The method used to remove lens distortion in this study was based on that proposed by Bouguet [25], where a series of images of a checkerboard or similar pattern is used to obtain the lens distortion of a camera at the desired focal length.

There are a variety of approaches used to determine the scaling factor for converting pixels to physical distance. In [26], a pre-testing calibration method is demonstrated. This involves setting up the camera in the laboratory in an identical manner to that of the field test to be carried out; that is, same monitoring distance, focal length, angle etc. The camera is calibrated using the checkerboard pattern and these variables are used to remove lens distortion and provide a scaling factor for the videos captured in the field trials. The formula to show this is as follows:

$$SF = \frac{d}{D} = \frac{f}{p \times Z}\left(\frac{pixel}{mm}\right) \quad (1)$$

where *SF* is the scaling factor ratio, *d* is a distance on the image, *D* is a world distance, *f* is the focal length of the camera, *p* is the unit length of the camera sensor (mm/pixel) and *Z* is the distance from the camera to the monitoring location. The scaling factor can also be determined from:

$$SF = \frac{D_{Known}}{I_{Known}} \quad (2)$$

where D_{Known} is the known physical length on the object surface and I_{Known} is the corresponding pixel length on the image plane.

2) Feature Extraction:

This is the process of extracting and detecting salient features from the images of the object to be tracked. Examples of these could be corners, rivets or natural decay in a bridge structure. Processing time can be minimized by only searching for features inside a Region of Interest (ROI). The process selected for use in the algorithm was SURF [27], a robust and computationally inexpensive extension of SIFT [28]. The key points provided by SURF are scale and rotation invariant and are detected using a Haar wavelet approximation of the blob (region in an image that differs in properties, such as brightness/colour, from surrounding regions) detector based on the Hessian determinant. These approximations are used in combination with integral images (the sum of pixel values in the image) to encode the distribution of pixel intensity values in the neighbourhood of the detected feature. The natural features detected in the laboratory tests are shown in Fig 4.These features consisted of irregularities in the surface of the beam that could be easily identified and tracked through the video.

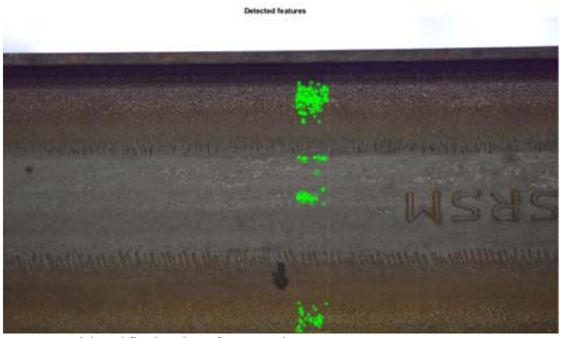

Fig 4 Features identified using feature detector

3) Feature Tracking:

On detection of the points, they must be tracked through subsequent frames to filter outliers and improve the dynamic estimation of displacement. Careful application of threshold values must be maintained during this process, as features may become occluded or vary during the progression of a video. The system in this research makes use of a Kanade-Lucas-Tomasi (KLT) [29] tracker to determine movement of the features detected. This method takes the points detected by the feature extractor and uses them for initialization. The system removes outliers using the statistically robust M-estimator SAmple Consensus (MSAC) algorithm [30] which is a variant of the RANSAC algorithm. The MSAC algorithm scores inliers according to the fitness of the model and uses this, together with a user-specified re-projection error distance, to minimize the usage of outliers in the displacement calculation. Any features that do not meet these thresholds are rejected, with the inliers then tracked on the next video frame using the KLT algorithm. The displacement of the object can be measured in pixels by calculating the relative movement between frames of the centroid of a matrix containing the extracted features. While it is possible to use SURF as a means of means of feature tracking as well as extraction, the results gathered in preliminary trials were not as accurate/stable compared to reference sensors as the results obtained using SURF & KLT in tandem, with undesirable variance in the number of features detected/tracked throughout a video compared to the tandem approach of SURF/KLT. Results from a laboratory investigation on this are shown in Fig 5 and Fig 6.

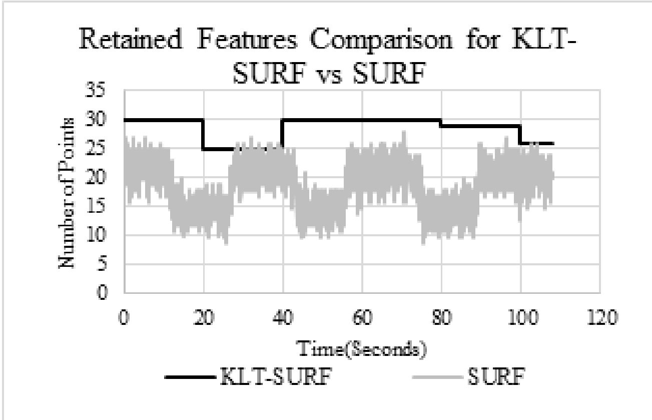

Fig 5 Retained Features Comparison for SURF vs KLT-SURF

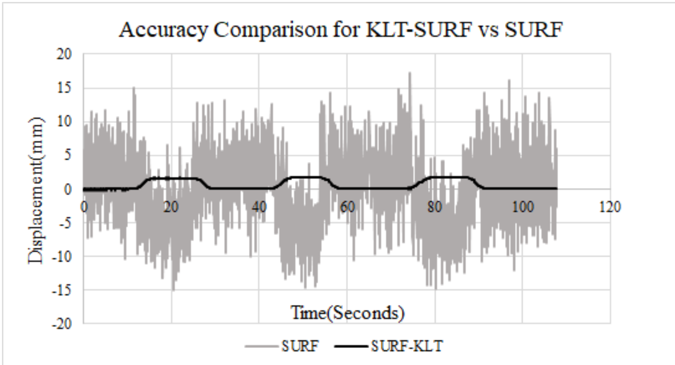

Fig 6 Accuracy Comparison for SURF vs KLT-SURF

The pixel movement is converted to engineering units using Eq. (2). This continues until all frames of the video have been processed.

IV. Experimental Programme

The aim of the experimental work was to conduct a series of sequential tests to establish the accuracy of the timecode synchronization between the vision sensors, since perfect synchronisation is required for a full characterisation of the deflection pattern

A. Test Series 1 – Timecode testing

The system for synchronizing the vision sensors involves attaching an accessory for the GoPro called Syncbac. The accessory embeds timecode data in each video. This metadata is then used to synchronize the videos so that they start at the same time. This is accurate to frame level at 30 FPS as the code embeds timecode data for synchronization in each frame. This was tested using a website called currentMillis.com, which displays the time elapsed in milliseconds since 1/1/1970. The cameras were placed 20 m apart and set to record this website displayed on separate computers. When the recordings were analysed and combined it was confirmed that each frame matched successfully. An example frame is shown in Fig 7. The test was carried out over a span of 45 minutes and the synchronization of the cameras was consistent throughout the video analysis, obtaining a perfect synchronisation after the 45 min.

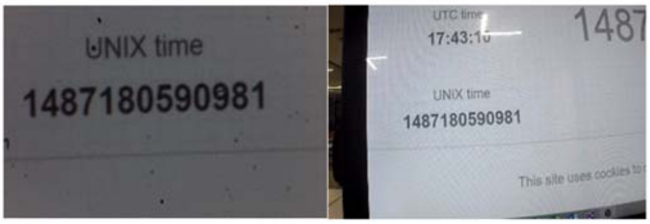

Fig 7 Readings from initial time synchronization trial, confirming accurate recording of UNIX time.

B. Test Series 2 – Accuracy of synchronized vision sensors for displacement measurement

The accuracy of the hardware system and associated post processing techniques were developed and validated through a laboratory experimental program. This involved tracking the displacement of a simply supported 178mm×102mm×19mm Universal Beam with a clear span of 5.3 m. A centrally applied static load of 3255N was applied to induce displacement along the span of the beam. The beam was split into 9 elements of equal length along the span of them beam to situate the loading and sensing points. The nodes connecting the elements were numbered 1-10 consecutively from left to right. Hence the load was applied midway between nodes 5 and 6.

1) Sensor configuration and data acquisition

Linear Variable Displacement Transducers (LVDT's) were used to validate the camera measurements at the monitoring locations used by the camera along the span. The LVDT sensors were configured to measure static displacements at each of the nodes monitored by the camera. A Datataker DT800 logger was used to acquire the readings at discrete times during the test corresponding to times when the beam was loaded and unloaded. The FOS was also used at a single node (Node 4) to validate the accuracy of the deflections that were determined from the camera readings. This sensor was used because it provides a high level of accuracy compared to LVDT. The FOS was positioned to record continuous displacement measurements at a rate of 25 Hz. The wavelength shift data associated with the FOS was recorded and converted to displacement using an approach described previously [31], where a Fabry-Perot filter was used in tandem with a photodiode.

Two GoPros set to record continuously during loading and unloading at a frame rate of 25 fps were used to monitor the beam. The GoPros were modified and fitted with C-mount and F-mount lenses to reduce lens distortion and provide greater flexibility in terms of monitoring distance. One camera was set to monitor node 3 and the second to monitor node 4. The readings taken at each node were converted from pixels to mm using the scaling factor of Equation (2).

The results from the synchronization trial for nodes 3 and 4 are shown in Fig 8. The results show good agreement between the camera system and the LVDT/FOS sensors, with our vision system outperforming the LVDT sensors in the point where the FOS was available.

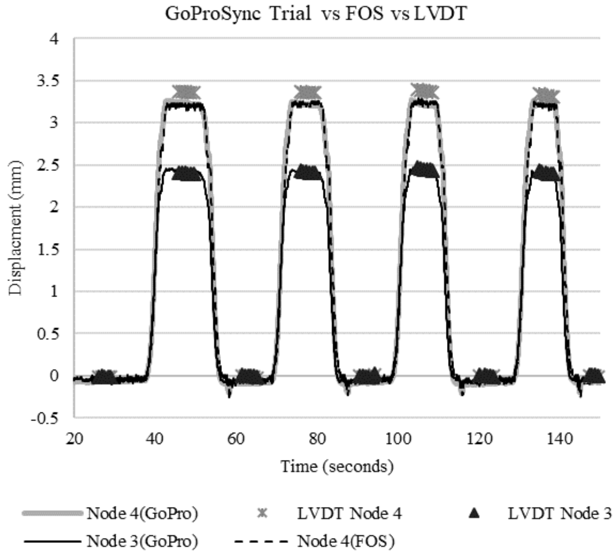

Fig 8 Vision, FOS and LVDT sensor displacement results for test series 2

To allow for accurate comparison between the displacement results calculated from the vision-based sensors and the validation sensors, the root mean square error (RMSE) is presented in Table I.

TABLE I
RESULTS FROM GOPRO VS FOS VS LVDT DISPLACEMENT MONITORING

Camera Node	Validation Sensor	RMSE (vision sensor v's validation sensor) (mm)
3	LVDT	0.044
4	LVDT	0.107
4	FOS	0.079

The correlation coefficient between the FO and the Vision results at Node 4 is .894 for this test.

The results confirm successful synchronization of the two cameras, providing confidence in this method for future deployment. It is believed by the authors that the higher RMSE with the LVDT comparison at Node 4 is due to the lower resolution of the LVDT versus the FOS. The low error results from the RMSE comparison validate the use of the GoPro camera in laboratory trials.

2) Scaling Factor Determination Trial

A supplementary laboratory trial was carried out between the dimension correspondences(DC), Catbas-Khuc(CK) and Bouquet(B) methods of scaling factor determination, the results are shown in Fig 9.

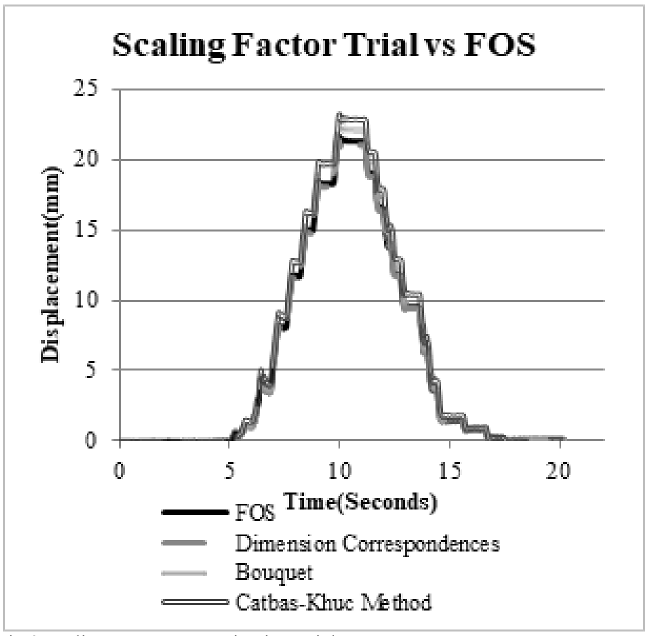

Fig 9 Scaling Factor Determination Trial

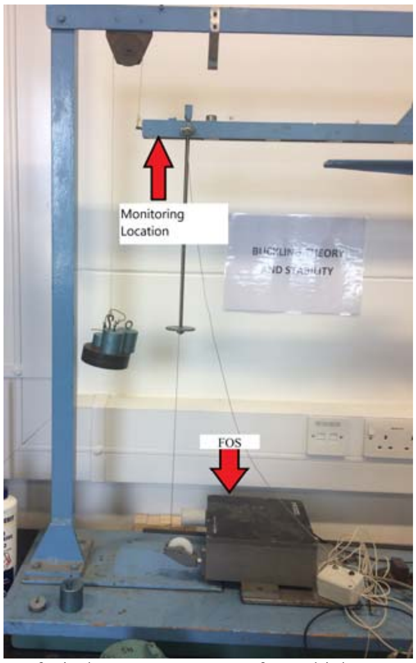

Fig 10 Setup of Displacement Apparatus for multiple cameras at single monitoring location trial

The correlation coefficient for each method was 1 when compared to the FOS, the Root Mean Square Error RMSE compared to FOS is shown in Table II.

TABLE II
RESULTS FROM SCALING FACTOR DETERMINATION TRIAL

Dimension Correspondences RMSE vs FOS(mm)	Catbas - Khuc RMSE vs FOS(mm)	Bouquet RMSE vs FOS(mm)
.0962	.7691	.3616

The superior accuracy gained from the use of dimension correspondences method (Equation (2)) resulted in its selection for use in this study.

3) Multiple Cameras at Single Monitoring Location Trial

An additional trial was carried out in the laboratory where two GoPro cameras set to 25fps were used to monitor the movement of a single target attached to a displacement testing apparatus while it was displaced manually. The cameras were placed 4.3m away from the monitoring location and pixel-mm conversion was carried out using dimension correspondences method in Eq. (2). Verification of the measured displacement was provided by the FOS to record at 25hz. The setup for this trial is shown in Fig 10, with the results shown in Fig 11 and summarised in Table III.

TABLE III
RESULTS: MULTIPLE CAMERAS AT A SINGLE MONITORING LOCATION

GoPro 1 RMSE vs FOS(mm)	GoPro 1 CC vs FOS	GoPro 2 RMSE vs FOS(mm)	GoPro 2 CC vs FOS	GoPro 1 CC vs GoPro 2
.1533	.9914	.0928	.9975	.9869

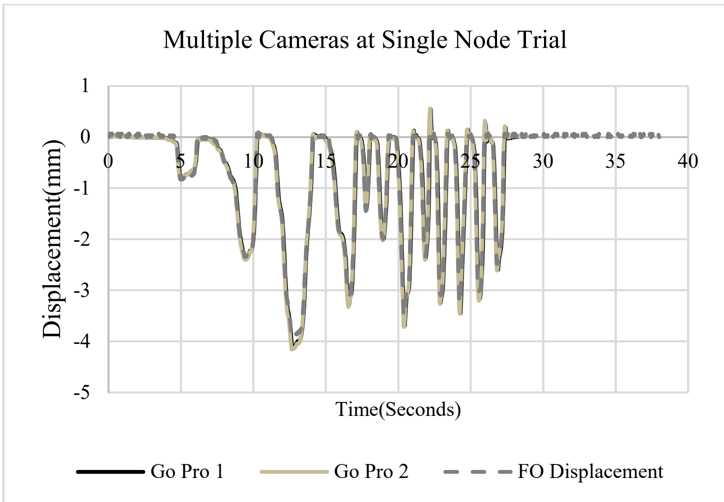

Fig 11 Results of Multiple Cameras at Single Node Trial

This trial provided confidence in the capabilities of the system for measuring displacement from multiple synchronised cameras.

4) Stationary Location Accuracy Trial

An additional metric for determining the quality of a displacement monitoring system is that of stability. To test this, a supplementary trial was carried out where one of the modified action cameras recorded images of a stationary portion of the testing setup to determine if the algorithm experienced any drifting away from true values over a longer monitoring time than previous tests. The results are shown in Fig 12.

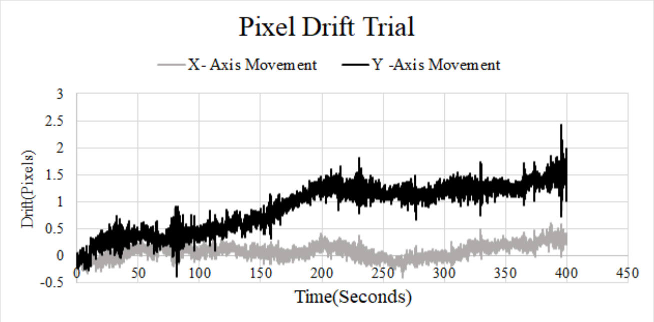

Fig 12 Results from Stability Trial

As can be seen from the results, there is a drift of only 2 pixels of a 4K video over the course of the trial in the Y-axis, with drift of 0.5 pixels in the x-axis.

C. Test Series 3 – Validation of different types of vision-based sensors

The purpose of this test series was to validate results using other camera types, thereby ensuring greater monitoring flexibility but also justifying the use of GoPro as the choice of sensor. For this, the Blink Hub app provided with the Syncbac was used for the camera control. A WIFI-enabled smart device can be paired with the pulse device and used to display the timecode in use by devices. This reference can then be displayed in the field of view of any camera type and used as a means of synchronizing videos. The centrally loaded beam from test series 2 was loaded and unloaded, similarly to test series 2, and a selection of nodes were monitored as detailed below. For this test a Nikon D810 camera with an 80-400mm zoom lens and a resolution of 1080p was used in addition to the Syncbac enabled GoPro.

1) Sensor configuration and data acquisition

For this test series, the reference timecode was obtained by manually reading the images (a text recognition algorithm could be used to automate this process in future). In this case the FOS was used as the sole means of validating the vision-based displacement. The cameras were both placed at a monitoring distance of 4.2 m and targeted the monitoring location at Node 7. Lenses and zoom levels were chosen to be as similar as possible, with small differenced due to availability and manufacturers, yielding to the pixel to millimetre conversion factors depicted in Table IV. An image from the D810 Camera used in the test is shown in Fig 13.

TABLE IV
MONITORING LOCATIONS FOR TEST SERIES 3

Test	GoPro Node	GoPro Pixel/mm Conversion Factor	D810 Node	D810 Pixel/mm Conversion Factor
3	7	0.1011 mm/pixel	7	0.1829 mm/pixel

The results are shown in Fig 14 and Table V. The data confirms that there is good agreement between the camera systems and the FOS.

Fig 13 D810 Image from Test 3

TABLE V
RESULTS: TEST SERIES 3 AT NODE 7

GoPro RMSE vs FOS(mm)	GoPro CC vs FOS	D810 RMSE vs FOS(mm)	D810 CC vs FOS	D810 CC vs GoPro
.0434	.9994	.0589	.9953	.9935

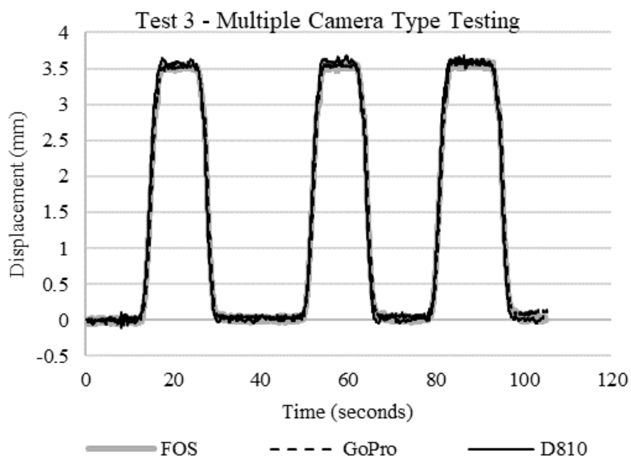

Fig 14 Results from Test 3 Run 1

This test has proven the effectiveness of the solution with multiple camera types, which increases the flexibility of our system to different sensors, according to the user's preferences and availability. The superior results obtained with the modified action camera system (approx. cost ~£500) vs the D810 (approx. cost ~£2500) also validate the use of the low-cost action camera as a means of gathering accurate deflection data.

V. Field Testing of System

On completion of the algorithm development and laboratory testing, a field test was carried out to determine the system's suitability for measuring the corresponding bridge displacement in real scenarios and perform a complex analysis, such as, for instance, accurately identifying vehicles and identifying the pattern of displacement along the span of the bridge. A single lane 30 m span steel truss bridge, illustrated in Fig 15, was selected as a suitable structure to test this system. 'Verners' bridge is on the Tamnamore Road in Co Tyrone, Northern Ireland. This road provides access to a busy industrial estate and is therefore frequently used by heavy goods vehicles (HGV's). Additionally, traffic on the bridge is controlled by a traffic light system which only allows for a single lane of traffic in one direction at any one time thus removing the complication of multiple events on the bridge (which is being addressed in ongoing research). Two GoPro cameras were used in this field test, to measure displacement at mid- and ¾-span and a third GoPro to identify the associated vehicles causing this deflection.

Fig 15 Side elevation of Verners Bridge. (Image taken from location of cameras monitoring deflection)

A. *Sensor configuration and data interpretation*

Bridge displacements were monitored using two GoPros mounted on a single tripod on the North West river bank at a monitoring distance of 22m. The cameras were adapted as described in III. The focal length of both lenses was set to 135mm with a wide field of view setting selected on the GoPros. Footage was captured at a framerate of 25fps. Natural image features at midspan (Figure 16) and 3/4span (Figure 17) were targeted for monitoring. A pixel-mm ratio was defined as 0.5911 mm/pixel at midspan; with a pixel-mm ratio of 0.6891mm/pixel determined at 3/4span allowing for sub-millimetre measurement of displacement on the bridge span at both locations. The lens used for this study has a capability to lock the focal length in place, which meant the parameters would be preserved to remove lens distortion after calibration. The camera to target distance/angle was measured using a laser distometer, and the calibration step was performed in identical circumstances (camera distance, focal length, etc) to the field trial on the premises of QUB.

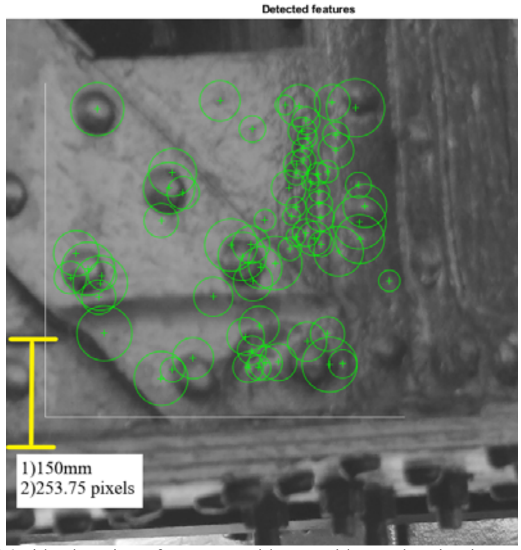

Figure 16 Side elevation of Verners Bridge at midspan showing image features. 1) is the distance in engineering units, with 2) the distance in pixels on captured footage. (Image taken from location of camera monitoring deflection)

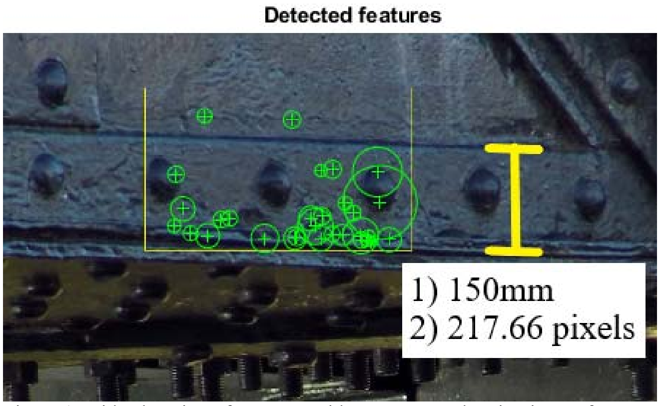

Figure 17 Side elevation of Verners Bridge at ¾ span showing image features. 1) is the distance in engineering units, with 2) the distance in pixels on captured footage. (Image taken from location of camera monitoring deflection)

Fig 18, Fig 19 and Fig 20 provide a sample of the data collected at this site. This confirms accurate camera synchronization and clear identification of displacements at both the mid- and ¾-span. The additional level of noise in the results for Fig 19 are due to multiple cars following close behind the vehicle being tracked.

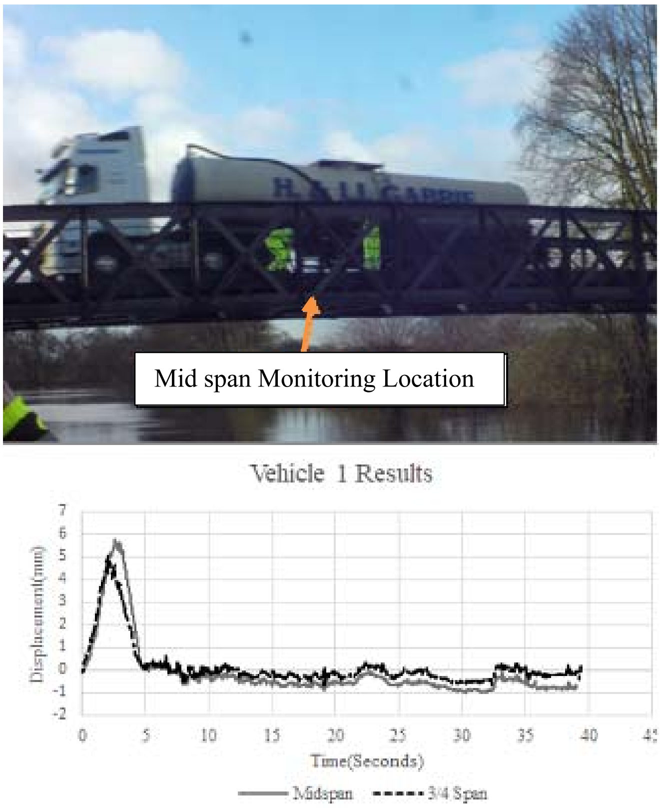

Fig 18 Vehicle 1 Crossing Verners Bridge & Results

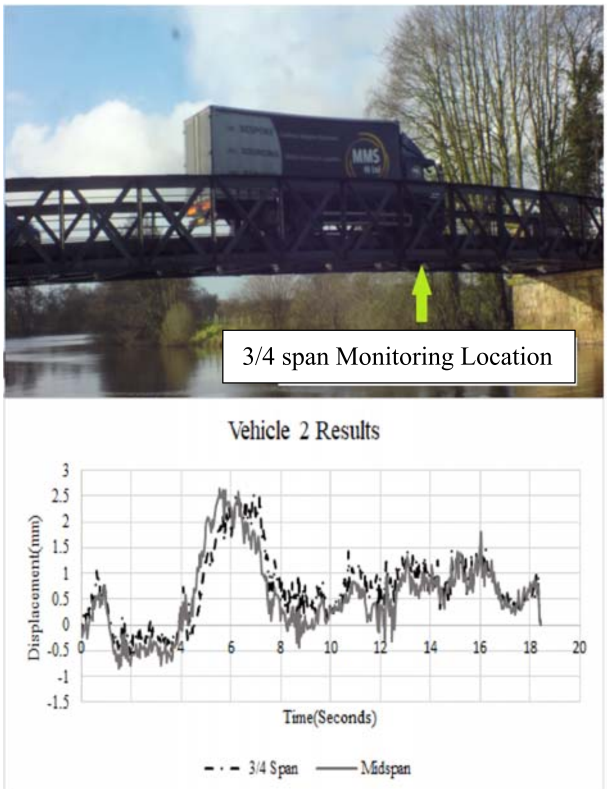

Fig 19 Vehicle 2 Crossing Verners Bridge & Results

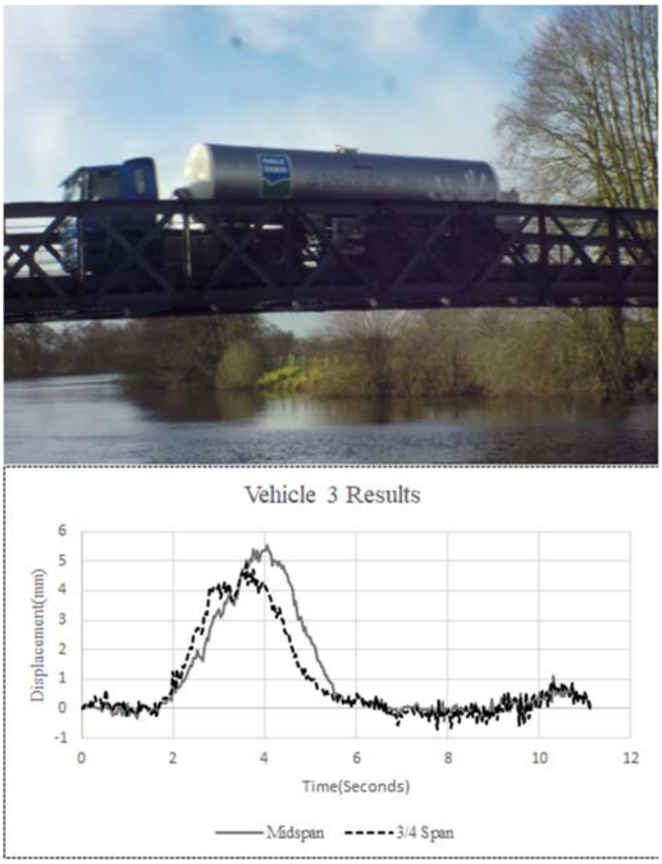

Fig 20 Vehicle 3 Crossing Verners Bridge & Results

As previously described, to assess the structural condition of the bridge, it is important to relate the measured displacements to the corresponding imposed traffic loading. Therefore, the accurate synchronization of the third camera to allow for successful traffic identification, was a key feature of this system. In each case the vehicle was easily identified, and an image has been provided along with the displacement data. In this initial field trial, the vehicles were manually identified. Work is currently in progress to develop a deep learning system for autonomous vehicle classification. This system would be able to identify and locate axle spacings of vehicles crossing the bridge, allowing for calculation of local and global responses of the bridge to crossing vehicles.

VI. Discussion and Conclusions

A sequential series of tests have been carried out to validate our fully synchronized wireless vision sensor monitoring system. Each of the tests carried out was designed to build upon the results of previous work and facilitated the development of an accurate algorithm for determining displacements from video footage.

A review of the existing literature highlights the need for a precise fully wireless monitoring system which could be rapidly deployed on a bridge of medium to long span. The systems presented overcome previous limitations in terms of cost and power consumption as well as in the size of the infrastructure due to the use of multiple vision sensors. The results from the initial synchronization trial are shown to be repeatable in the field and successful millisecond timecode synchronization was consistently obtained. Test Series 2 offered a robust testing programme which provided confidence in the displacement calculation algorithm used in the post processing of the vision sensors. In comparison to a FOS, displacement from the vision sensor repeatedly correlated with loading pattern and displacement magnitude. Significant advantages of the vision sensor over the FOS include, but are not limited to, the contactless nature of measurement, no requirement for a power supply on site and cost. A single FOS costs five times that of a single vision sensor.

Test 3 confirms that the system can be adapted to include multiple camera types. This key feature of the system would be particularly useful for the incorporation of existing camera networks into the SHM system presented here.

In summary the work carried out in the experiential trials gave confidence in the accuracy of the system. This allowed for rapid deployment on site and minimized the equipment needed for site measurement.

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